## 2 Müntz-Jackson Theorems

## Recall:

• Density properties of Müntz polynomials.

Theorem (Theorem 1.1 in [Lorentz (1996)]).

Let  $\Lambda_{\infty} = \{0 = \lambda_0 < \lambda_1 < \dots < \lambda_n < \infty\}$  with  $\lambda_n \to \infty$ . Then the Müntz space  $\mathcal{M}(\Lambda_{\infty})$  is dense in each of the spaces C[0,1] or  $L_p[0,1]$ ,  $1 \le p < \infty$  if and only if

$$\sum_{k=1}^{\infty} \frac{1}{\lambda_k} = \infty.$$

The density property can be indeed extended in several ways: unsorted sequences (which may result in distinct cluster points), complex sequences, and intervals away from the origin.

Under this iff condition, the sequence  $\Lambda_{\infty}$  can be generalized as

$$\begin{cases} \lambda_0 \geqslant 0 \text{ and } \{\lambda_k\}_{k=1}^{\infty} \text{ with } \inf_{k\geqslant 1} \{\lambda_k\} > 0, & \text{for } L_p[0,1] \text{ with } 1\leqslant p < \infty; \\ \lambda_0 = 0 \text{ and } \{\lambda_k\}_{k=1}^{\infty} \text{ with } \inf_{k\geqslant 1} \{\lambda_k\} > 0, & \text{for } C[0,1] \text{ with } p = \infty. \end{cases}$$

But its proof requires some techniques and discussions in the cases of distinct cluster points (see [Borwein (1995), Sec. 4.2] or [Almira (2007), Sec. 3.1]).

•  $L_p$ -Best Approximation by Müntz Polynomials. Let  $f \in L_p[0,1]$  if  $1 \leq p < \infty$  (or C[0,1] if  $p = \infty$ ). The error of approximation from  $\mathcal{M}(\Lambda_n)$  to f is

$$E(f, \Lambda_n)_p := \inf_{M \in \mathcal{M}(\Lambda_n)} ||f - M||_{L_p[0,1]}.$$

Note that C[0,1] with  $L_{\infty}$ -norm is completed since it reduces to **maximum norm**. In fact, when  $p = \infty$ , for  $f \in C[0,1]$  we have

$$||f||_{\infty} := \inf\{C : |f(x)| \leqslant C \text{ a.e. on } [0,1]\} = \inf_{\substack{mF_0 = 0 \\ F_0 \subset [0,1]}} \left\{ \sup_{x \in [0,1] \setminus F_0} |f(x)| \right\} = \max_{0 \leqslant x \leqslant 1} \{|f(x)|\},$$

where  $mF_0 = 0$  denotes that the Lebesgue measure of  $F_0$  is 0.

### Schedule:

We consider the  $L_p$  best approximation (or Jackson Theorems in Sec. 2) in several subsections:

- 1. Existence and uniqueness of  $L_p$  best approximation.
- 2. Error of approximation for monomial  $x^r$ , and dense properties.
- 3. Error of approximation for  $f \in W_p^1[0,1]$ , and some corollaries.

## **Notation Convention:**

- AuxThm refers to the auxiliary theorem, which is not included in this book, similar to AuxCor, AuxLem, and other related terms.
- Denote  $\Lambda_{\infty} = \{0 = \lambda_0 < \lambda_1 < \dots < \lambda_n < \dots \}$  with  $\lim_{n \to \infty} \lambda_n = \infty$ .
- Denote  $\Lambda_n = \{0 = \lambda_0 < \lambda_1 < \dots < \lambda_n\}$  simply by  $\Lambda$ , where the integer  $n \ge 1$  is fixed.
- Denote the linear space  $\mathcal{M}(\Lambda_n) = \operatorname{span}\{x^{\lambda_0}, \dots, x^{\lambda_n}\}$ , associated to  $\Lambda_n$ , with respect to the field of real numbers  $\mathbb{R}$ .
- $E(f, \Lambda_n)_p = \inf_{M \in \mathcal{M}(\Lambda_n)} \|f M\|_p$ , where  $\|\cdot\|_p$  stands for the  $L_p[0, 1]$  norm for  $1 \leq p \leq \infty$ .

# 2.1 Existence and uniqueness of $L_p$ -best approximation.

Let  $(X, \|\cdot\|)$  be a Banach space with **real or complex** scalars, and  $X_n \subset X$  be its finite dimensional linear subspace. The *best approximation* to  $f \in X$  from  $X_n$  is defined as

$$E(f) := \inf_{p \in X_n} ||f - p||.$$

**AuxThm 2.1** (Theorem 1.1, p.59, [Lorentz (1993)]). For each  $f \in X$ , there exists a best approximation to f from  $X_n$ .

*Proof.* Let F(p) = ||f - p||,  $\forall p \in X_n$ . Let the **closed and bounded** set  $C = \{p \in X_n : F(p) \leq ||f||\}$ . Then that F(p) attains its minimum over  $X_n$  is equivalent to attain the minimum over C, that is

$$\inf_{p \in X_n} \|f - p\| = \inf_{p \in C} \|f - p\|.$$

Thus the existence is obvious since C is **compact** and F(p) is **continuous**.

**AuxThm 2.2.** If X is strictly convex, which is characterized by

$$\left\{ \begin{array}{ll} \forall f_1 \neq f_2, & \|f_1\| = \|f_2\| = 1, \quad \alpha_1, \alpha_2 > 0, \quad \alpha_1 + \alpha_2 = 1, \\ imply & \|\alpha_1 f_1 + \alpha_2 f_2\| < 1. \end{array} \right.$$

Then the best approximation to  $f \in X$  from  $X_n$  is **unique**.

Proof. Suppose that there are  $p_1, p_2 \in X_n$  such that  $||f - p_1|| = ||f - p_2|| = E(f)$ . If E(f) = 0, then  $||p_1 - p_2|| \le ||f - p_1|| + ||f - p_2|| = 2E(f) = 0$ , which implies  $p_1 = p_2$ . If E(f) > 0, we prove it by supposing that  $p_1 \ne p_2$ , which leads to a contradiction:

$$E(f) \le \left\| f - \frac{1}{2}(p_1 + p_2) \right\| = \left\| \frac{1}{2}(f - p_1) + \frac{1}{2}(f - p_2) \right\| < E(f).$$

**AuxLem 2.1.**  $L_p[a,b]$  is strictly convex for 1 .

*Proof.* For any  $f_1 \neq f_2$ ,  $||f_1||_p = ||f_2||_p = 1$ ,  $\alpha_1, \alpha_2 > 0$ ,  $\alpha_1 + \alpha_2 = 1$ , then by Minkowski's inequality (or triangle inequality):

$$\|\alpha_1 f_1 + \alpha_2 f_2\|_p < \alpha_1 \|f_1\|_p + \alpha_2 \|f_2\|_p = 1.$$

The equality for  $1 if and only if <math>f_1$  and  $f_2$  are **positively linearly dependent**, that is,  $f_1 = \lambda f_2$  for some  $\lambda \ge 0$  or  $f_2 = 0$ . This is impossible since  $f_1 \ne f_2$  and  $||f_1|| = ||f_2|| = 1$ .  $\square$ 

**Remark 2.1.** Both  $L_1[a,b]$  and  $L_{\infty}[a,b]$  are **not** strictly convex.

Remark 2.2. When we consider vectors in  $\mathbb{R}^2$ , the strictly convex property for  $L_p$  is visualizable. Let  $\mathbf{x} = [x_1, x_2]$ .

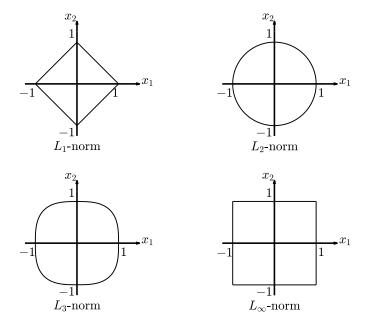


Figure 1: Unit circles in  $\mathbb{R}^2$  with different  $L_p$ -norms. Download the Figure and Code.

# **AuxThm 2.3.** Let X = C[a,b] and $X_n \subset X$ satisfy the **Haar condition**:

For any basis  $\{\phi_i(x)\}_{i=1}^n$  of  $X_n$  and any set of distinct points  $\{\xi_i\}_{i=1}^n \subset [a,b]$ , it follows that

$$\begin{bmatrix} \phi_1(\xi_1) & \cdots & \phi_1(\xi_n) \\ \vdots & & \vdots \\ \phi_n(\xi_1) & \cdots & \phi_n(\xi_n) \end{bmatrix} \text{ is non-singular.}$$

Then for any  $f \in X$ , there is just one  $L_1$  (or  $L_{\infty}$ ) best approximation to f from  $X_n$ .

*Proof.* The  $L_1$ -best approximation, see [Powell (1981), Theorem 14.3, p.170], while  $L_{\infty}$ -best approximation, see [Powell (1981), Theorem 7.6, p.80].

### 2.2 Error of approximation for monomial $x^r$ .

### Schedule of this Subsection:

- Prove that  $E(x^r, \Lambda)_2$  (Eq. (2.1)) and  $\mathcal{M}(\Lambda_{\infty})$  is dense in  $L_2[0, 1]$ ;
- Prove that  $E(x^r, \Lambda)_{\infty}$  (Eq. (2.2)) and  $\mathcal{M}(\Lambda_{\infty})$  is dense in C[0, 1];
- Prove that  $E(x^r, \Lambda)_p$   $(2 (Theorem 2.2) and <math>\mathcal{M}(\Lambda_\infty)$  is dense in  $L_p[0, 1]$ .

## **2.2.1** Case 1: p = 2.

Our goal is to prove (2.1) in [Lorentz (1996)], which is stated as following theorem:

**AuxThm 2.4** (see also Theorem 5.4 in [Lorentz (1993)]). For r > -1/2,  $\Lambda = {\lambda_0, \lambda_1, \dots, \lambda_n}$  with distinct elements and  $\lambda_k > -1/2$ ,  $k = 0, 1, \dots, n$ , we have

$$E(x^r, \Lambda)_2 = \frac{1}{\sqrt{2r+1}} \prod_{k=0}^n \frac{|r - \lambda_k|}{|r + \lambda_k + 1|}.$$

### Preliminaries.

In a **real** Hilbert space  $(H, (\cdot, \cdot))$  with its norm induced by  $||f|| = \sqrt{(f, f)}$ , let  $f_1, \dots, f_n \in H$  be linearly independent elements, and let  $X_n := \text{span}\{f_1, \dots, f_n\}$ .

**AuxThm 2.5.** For  $g \in H$ , there is a unique  $f \in X_n$  such that

$$||g - f|| = \inf_{p \in X_n} ||g - p||.$$

*Proof.* Existence is obvious and uniqueness follows from that Hilbert space is strictly convex, see details.  $\Box$ 

We call f the best approximation of g from  $X_n$  in H.

**AuxCor 2.1.** Let f be the best approximation of g, then it is equivalent to the orthogonal projection: (g - f, p) = 0,  $\forall p \in X_n$ .

Proof. ( $\Leftarrow$ ) Let f be the orthogonal projection of g onto  $X_n$ , i.e., (g-f,p)=0,  $\forall p \in X_n$ . Then  $\|g-p\|^2 = \|g-f+f-p\|^2 = \|g-f\|^2 + \|f-p\|^2 \geqslant \|g-f\|^2$ .

Thus f is the best approximation.

 $(\Rightarrow)$  Let f satisfy  $||g-f|| = \inf_{p \in X_n} ||g-p||$ . For any  $p \in X_n$ , let

$$h(t) = ||g - (f + tp)||^2 = ||g - f||^2 - 2t(g - f, p) + t^2||p||^2$$

Since h(t) achieves its minimum at t=0, then h'(0)=0, which leads to (g-f,p)=0.

**AuxLem 2.2.** The distance of best approximation  $d := \inf_{p \in X_n} \|g - p\|$  is given by

$$d^2 = \frac{G(g, f_1, \cdots, f_n)}{G(f_1, \cdots, f_n)},$$

where G is the Gram determinant

$$G(f_1, \dots, f_n) = \left| \begin{array}{ccc} (f_1, f_1) & \cdots & (f_1, f_n) \\ \vdots & & \vdots \\ (f_n, f_1) & \cdots & (f_n, f_n) \end{array} \right|.$$

*Proof.* The best approximation  $f \in X_n$  to g satisfies (g - f, p) = 0,  $\forall p \in X_n$ . Now we suppose that  $f = \sum_{i=1}^n a_i f_i$ , then

$$\sum_{i=1}^{n} a_i(f_i, f_k) = (g, f_k), \quad k = 1, 2, \dots, n.$$
 (1)

On the other hand, since (g-f,f)=0,  $d^2=(g-f,g-f)=(g,g-f)=(g,g)-(g,f)$ , we have

$$\sum_{i=0}^{n} a_i(g, f_i) = (g, g) - d^2.$$
(2)

Hence combining (1) with (2) we have

$$\begin{bmatrix} 1 & (g, f_1) & \cdots & (g, f_n) \\ 0 & (f_1, f_1) & \cdots & (f_n, f_1) \\ \vdots & \vdots & & \vdots \\ 0 & (f_1, f_n) & \cdots & (f_n, f_n) \end{bmatrix} \begin{bmatrix} d^2 \\ a_1 \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} (g, g) \\ (g, f_1) \\ \vdots \\ (g, f_n) \end{bmatrix},$$

and by Cramer's rule,

$$d^2 = \frac{G(g, f_1, \cdots, f_n)}{G(f_1, \cdots, f_n)}.$$

**Remark 2.3.**  $G(f_1, \dots, f_n) \neq 0$  if and only if  $f_1, \dots, f_n$  are linearly independent.

Remark 2.4. AuxThm 2.5, AuxCor 2.1, and AuxLem 2.2 provide a general framework to compute error estimation of best approximation in a Hilbert space.

**AuxLem 2.3** (Cauchy's determinant). For real numbers  $a_i$  and  $b_k$  that satisfy  $a_i + b_k \neq 0$ ,  $1 \leq i, k \leq n$ , we have

$$\begin{vmatrix} \frac{1}{a_1+b_1} & \cdots & \frac{1}{a_1+b_n} \\ \vdots & & \vdots \\ \frac{1}{a_n+b_1} & \cdots & \frac{1}{a_n+b_n} \end{vmatrix} = \frac{\prod_{n \geqslant i > k \geqslant 1} (a_i - a_k)(b_i - b_k)}{\prod_{1 \leqslant i,k \leqslant n} (a_i + b_k)}.$$

*Proof.* We denote  $D(n) = \det[1/(a_i + b_k)]_{1 \le i,k \le n}$ . We subtract the last row of D(n) from each of the other rows, and then we can factor out from D(n) by  $1, \ldots, n-1$  rows and  $1, \ldots, n$  columns

$$D(n) = \begin{vmatrix} \frac{1}{a_1+b_1} & \cdots & \frac{1}{a_1+b_n} \\ \vdots & & \vdots \\ \frac{1}{a_{n-1}+b_1} & \cdots & \frac{1}{a_{n-1}+b_n} \\ 1 & \cdots & 1 \end{vmatrix} \cdot \frac{\prod_{i=1}^{n-1} (a_n - a_i)}{\prod_{i=1}^n (a_n + b_k)}.$$

Next we subtract the last column from each of the other columns, and extract the factors by  $1, \ldots, n-1$  rows and  $1, \ldots, n-1$  columns

$$D(n) = \begin{vmatrix} \frac{1}{a_1 + b_1} & \cdots & \frac{1}{a_1 + b_{n-1}} & \frac{1}{a_1 + b_n} \\ \vdots & & \vdots & \\ \frac{1}{a_{n-1} + b_1} & \cdots & \frac{1}{a_{n-1} + b_{n-1}} & \frac{1}{a_{n-1} + b_n} \\ 0 & \cdots & 0 & 1 \end{vmatrix} \cdot \frac{\prod_{i=1}^{n-1} (a_n - a_i)}{\prod_{i=1}^n (a_n + b_k)} \cdot \frac{\prod_{k=1}^{n-1} (b_n - b_k)}{\prod_{i=1}^{n-1} (a_i + b_n)}.$$

Therefore

$$D(n) = D(n-1) \cdot \frac{\prod_{k=1}^{n-1} (a_n - a_k)(b_n - b_k)}{(a_n + b_n) \prod_{k=1}^{n-1} (a_k + b_n)(a_n + b_k)},$$

by the induction we complete the proof.

*Proof of AuxThm 2.4.* Note that for  $\lambda, \mu > -1/2$ , we have

$$(x^{\lambda}, x^{\mu})_{L_2(0,1)} = \frac{1}{\lambda + \mu + 1}.$$

Then the theorem follows from

$$G(x^{\lambda_0}, \cdots, x^{\lambda_n}) = \frac{\prod_{n \geqslant i > k \geqslant 0} (\lambda_i - \lambda_k)^2}{\prod_{i=0}^n \prod_{k=0}^n (\lambda_i + \lambda_k + 1)},$$

and

$$G(x^r, x^{\lambda_0}, \dots, x^{\lambda_n}) = G(x^{\lambda_0}, \dots, x^{\lambda_n}) \cdot \frac{\prod_{k=0}^n (r - \lambda_k)^2}{(2r+1) \prod_{k=0}^n (r + \lambda_k + 1)^2}.$$

**Theorem** (Part of Theorem 1.1). Let  $\Lambda_{\infty} = \{0 = \lambda_0 < \lambda_1 < \dots < \lambda_n < \dots\}$  and  $\lim_{n \to \infty} \lambda_n = \infty$ . Then  $\mathcal{M}(\Lambda_{\infty})$  is dense in  $L_2[0,1]$  if and only if  $\sum_{k=1}^{\infty} \lambda_k^{-1} = \infty$ .

**Remark 2.5.** Let  $a_k > -1$ , the convergence or divergence of infinity product can be related to infinity sum:

•  $\prod_k (1 + a_k)$  converges if and only if  $\sum_k \log(1 + a_k)$  converges.

•  $\prod_k (1+a_k)$  diverges to 0  $(or +\infty)$  if and only if  $\sum_k \log(1+a_k)$  diverges to  $-\infty$   $(or +\infty)$ .

*Proof.* We note that the space of algebraic polynomials  $\mathbb{P}$  is dense in  $L_2[0,1]$ . It is sufficient to show that

$$\forall r \in \mathbb{N} = \{0, 1, 2, \dots\}, \lim_{n \to \infty} E(x^r, \Lambda_n)_2 = 0 \iff \sum_{k=1}^{\infty} \frac{1}{\lambda_k} = \infty.$$

" $\Leftarrow$ " Sufficiency. Suppose that  $\sum_{n=1}^{\infty} \lambda_n^{-1} = \infty$  and  $r \in \mathbb{N} \setminus \Lambda_{\infty}$ . Note that  $0 \in \Lambda_{\infty}$ , thus  $r \geqslant 1$ . There exists an index  $k_0$  s.t.  $\lambda_k > r$  whenever  $k \geqslant k_0$ . Then

$$\lim_{n \to \infty} E(x^r, \Lambda_n)_2 = \frac{1}{\sqrt{2r+1}} \frac{\prod_{k=0}^{\infty} |r - \lambda_k|}{\prod_{k=0}^{\infty} |r + \lambda_k + 1|} = C(r, k_0) \frac{\prod_{k=k_0}^{\infty} \left(1 - \frac{r}{\lambda_k}\right)}{\prod_{k=k_0}^{\infty} \left(1 + \frac{r+1}{\lambda_k}\right)},$$

where

$$C(r, k_0) = \frac{1}{\sqrt{2r+1}} \prod_{k=0}^{k_0 - 1} \frac{|r - \lambda_k|}{|r + \lambda_k + 1|}.$$

Denote

$$S_1 = \sum_{k=k_0}^{\infty} \log\left(1 - \frac{r}{\lambda_k}\right), \ S_2 = \sum_{k=k_0}^{\infty} \log\left(1 + \frac{r+1}{\lambda_k}\right).$$

Then  $S_1$  diverges to  $-\infty$  (or the positive series  $-S_1$  diverges to  $+\infty$ ), if and only if the positive series

$$\sum_{k=k_0}^{\infty} \frac{r}{\lambda_k} = +\infty.$$

Similarly,  $S_2$  diverges to  $\infty$  if and only if the positive series

$$\sum_{k=k_0}^{\infty} \frac{r+1}{\lambda_k} = \infty.$$

Then  $\lim_{n\to\infty} E(x^r, \Lambda_n)_2 = 0$  is obtained.

" $\Rightarrow$ " Necessity. Otherwise, we suppose that  $\sum_{k=1}^{\infty} \lambda_k^{-1} < \infty$ . Then  $S_1$  converges to a value ( $\neq 0$ ), and  $S_2$  converges to a value ( $\neq 0$ ). Hence  $\lim_{n\to\infty} E(x^r, \Lambda_n)_2 \neq 0$  leads to a contradiction.  $\square$ 

**Remark 2.6.** The value  $\lambda_0 = 0$  can be removed. In fact, let  $\Lambda_{\infty} = \{0 < \lambda_1 < \dots < \lambda_n < \dots \}$  with  $\lim_{n \to \infty} \lambda_n = +\infty$ , then

$$\lim_{n \to \infty} E(1, \Lambda_n)_2 = 0 \iff \prod_{k=1}^{\infty} \left( 1 - \frac{1}{\lambda_k + 1} \right) = 0 \iff \sum_{k=1}^{\infty} \log \left( 1 - \frac{1}{\lambda_k + 1} \right) = -\infty$$

$$\iff \sum_{k=1}^{\infty} \frac{1}{\lambda_k + 1} = +\infty \iff \sum_{k=1}^{\infty} \frac{1}{\lambda_k} = +\infty.$$

#### **2.2.2** Case 2: $p = \infty$ .

Our goal is to prove the (2.2) in [Lorentz (1996)], which is stated as following theorem:

**AuxThm 2.6** (Theorem 5.5 in [Lorentz (1993)]). For r > 0,  $\Lambda = \{\lambda_1, \lambda_2, \dots, \lambda_n\}$  with  $\lambda_k > 0$ ,  $k = 1, \dots, n$ , we have

$$E(x^r, \Lambda)_{\infty} \leqslant \prod_{k=1}^n \frac{|r - \lambda_k|}{r + \lambda_k}.$$
 (3)

*Proof.* For any M > 0 (it will be determined later), we put  $\bar{r} = Mr$  and  $\mu_k = M\lambda_k$ . For any coefficients  $c_k \in \mathbb{R}$ , we set

$$b_k = \frac{\bar{r} + 1/2}{\mu_k + 1/2} c_k, \ k = 1, 2, \dots, n,$$

and obtain

$$x^{\bar{r}+1/2} - \sum_{k=1}^{n} b_k x^{\mu_k + 1/2} = \left(\bar{r} + \frac{1}{2}\right) \int_0^x \left[ t^{\bar{r}-1/2} - \sum_{k=1}^{n} c_k t^{\mu_k - 1/2} \right] dt.$$
 (4)

Since  $\mu_k - 1/2 > -1/2$ ,  $k = 1, \dots, n$ , by AuxThm 2.4 we can select  $c_k$  to satisfy

$$\left\| t^{\overline{r}-1/2} - \sum_{k=1}^{n} c_k t^{\mu_k - 1/2} \right\|_{L^2(0,1)} = \frac{1}{\sqrt{2\overline{r}}} \prod_{k=1}^{n} \frac{|\overline{r} - \mu_k|}{\overline{r} + \mu_k}.$$

Then by Cauchy-Schwarz inequality and (4), we have  $\forall x \in [0,1]$  and M>0

$$\left| x^{\bar{r}+1/2} - \sum_{k=1}^{n} b_k x^{\mu_k + 1/2} \right| \leqslant \left( \bar{r} + \frac{1}{2} \right) \sqrt{x} \left\| t^{\bar{r}-1/2} - \sum_{k=1}^{n} c_k t^{\mu_k - 1/2} \right\|_{L^2(0,1)},$$

which leads to

$$\left| x^{Mr} - \sum_{k=1}^{n} b_k x^{M\lambda_k} \right| \leqslant \frac{Mr + 1/2}{\sqrt{2Mr}} \prod_{k=1}^{n} \frac{|r - \lambda_k|}{r + \lambda_k}. \tag{5}$$

By choosing M = 1/(2r) and taking the transform  $u = x^{1/(2r)}$  on (5), we have  $\forall u \in [0,1]$ 

$$\left| u^r - \sum_{k=1}^n b_k u^{\lambda_k} \right| \leqslant \prod_{k=1}^n \frac{|r - \lambda_k|}{r + \lambda_k},$$

which give rise to (3).

**Theorem** (Part of Theorem 1.1). Let  $\Lambda_{\infty} = \{0 = \lambda_0 < \lambda_1 < \dots < \lambda_n < \dots\}$  and  $\lim_{n \to \infty} \lambda_n = \infty$ . Then  $\mathcal{M}(\Lambda_{\infty})$  is dense in C[0,1] if and only if  $\sum_{k=1}^{\infty} \lambda_k^{-1} = \infty$ .

Remark 2.7.  $\lambda_0 = 0$  must be included in  $\Lambda_{\infty}$ .

*Proof.* We note that  $\mathbb{P}$  is dense in C[0,1]. It is sufficient to show that

$$\forall r \in \mathbb{N} = \{0, 1, 2, \cdots\}, \ \lim_{n \to \infty} E(x^r, \Lambda_n)_{\infty} = 0 \iff \sum_{k=1}^{\infty} \frac{1}{\lambda_k} = \infty.$$

" $\Leftarrow$ " Sufficiency. Suppose that  $\sum_{n=1}^{\infty} \lambda_n^{-1} = \infty$  and  $r \in \mathbb{N} \setminus \Lambda_{\infty}$ . Note that  $0 \in \Lambda_{\infty}$ , thus  $r \geqslant 1$ . There exists an index  $k_0$  s.t.  $\lambda_k > r$  whenever  $k \geqslant k_0$ . Then

$$\lim_{n\to\infty} E(x^r, \Lambda_n)_{\infty} \leqslant \prod_{k=1}^{\infty} \frac{|r-\lambda_k|}{r+\lambda_k} = C(r, k_0) \frac{\prod_{k=k_0}^{\infty} \left(1-\frac{r}{\lambda_k}\right)}{\prod_{k=k_0}^{\infty} \left(1+\frac{r}{\lambda_k}\right)}, \text{ where } C(r, k_0) = \prod_{k=1}^{k_0-1} \frac{|r-\lambda_k|}{|r+\lambda_k|}.$$

Denote

$$S_1 = \sum_{k=k_0}^{\infty} \log\left(1 - \frac{r}{\lambda_k}\right), \ S_2 = \sum_{k=k_0}^{\infty} \log\left(1 + \frac{r}{\lambda_k}\right).$$

Then  $S_1$  diverges to  $-\infty$  and  $S_2$  diverges to  $+\infty$ , leading to  $\lim_{n\to\infty} E(x^r, \Lambda_n)_{\infty} = 0$ .

" $\Rightarrow$ " Necessity. Note that

$$E(x^r, \Lambda_n)_{\infty} \geqslant E(x^r, \Lambda_n)_2$$
.

Then  $\forall r \in \mathbb{N}$ ,  $\lim_{n \to \infty} E(x^r, \Lambda_n)_{\infty} = 0$  gives rise to  $\lim_{n \to \infty} E(x^r, \Lambda_n)_2 = 0$ , which leads to  $\sum_{k=1}^{\infty} \lambda_k^{-1} = \infty$ .

## **2.2.3** Case 3: 2 .

Our goal is to prove the Theorem 2.2 in [Lorentz (1996)]:

**Theorem 2.2** (Theorem 2.2 in [Lorentz (1996)]). Let  $2 and <math>\Lambda = \{\lambda_0, \lambda_1, \dots, \lambda_n\}$  with distinct elements and  $\lambda_k > -1/p$ . For any  $r > -\frac{1}{p}$ , we have

$$E(x^r, \Lambda)_p \leqslant \frac{1 + 1/p}{(2r + 2/p)^{1/p}} \prod_{k=0}^n \frac{|r - \lambda_k|}{r + \lambda_k + 2/p}.$$
 (2.4)

**Lemma 2.1** (Lemma 2.1 in [Lorentz (1996)]). Let  $1 \leqslant q and let <math>-\frac{1}{q} < \ell_0 < \ell_1 < \cdots < \ell_n$ . For arbitrary real numbers  $a_0, a_1, \cdots, a_n$  and

$$b_k := \frac{1 + \ell_k + \frac{1}{p}}{1 + \frac{1}{p}} a_k, \quad 0 \leqslant k \leqslant n,$$

we have

$$\left\| x^{\frac{1}{q} - \frac{1}{p}} - \sum_{k=0}^{n} a_k x^{\ell_k + \frac{1}{q} - \frac{1}{p}} \right\|_p \leqslant \left( 1 + \frac{1}{p} \right) \left\| 1 - \sum_{k=0}^{n} b_k x^{\ell_k} \right\|_q. \tag{2.3}$$

*Proof.* Let us denote  $K := 1 + \frac{1}{p}$  and for  $0 < x \le 1$ 

$$Q(x) := \sum_{k=0}^{n} b_k x^{\ell_k}, \quad h(x) := x^{\frac{1}{p}} (1 - Q(x)),$$
$$g(x) := K x^{\frac{1}{q} - 1 - \frac{2}{p}} \int_0^x h(t) dt.$$

One easily verifies that g is the function on the left hand side of (2.3). Our goal is to show

$$||g||_p \leqslant K||1 - Q(x)||_q.$$

To achieve this goal, we employ Hölder type inequalities.

Hölder inequality: Let  $\Omega$  be a measure space, for any  $1 \leq p, q \leq \infty$  that satisfy  $\frac{1}{p} + \frac{1}{q} = 1$ . Suppose that  $f \in L_p(\Omega)$  and  $g \in L_q(\Omega)$ , then  $fg \in L_1(\Omega)$  and

$$||fg||_{L_1(\Omega)} \le ||f||_{L_n(\Omega)} ||g||_{L_q(\Omega)}.$$

Firstly, by Hölder's inequality, we have for  $0 < x \le 1$ ,

$$|g(x)| \leq Kx^{\frac{1}{q}-1-\frac{2}{p}} \int_{0}^{x} |h(t)| dt \leq Kx^{\frac{1}{q}-1-\frac{2}{p}} \left( \int_{0}^{x} 1 dt \right)^{1-\frac{1}{q}} \left( \int_{0}^{x} |h(t)|^{q} dt \right)^{\frac{1}{q}}$$

$$= Kx^{-\frac{2}{p}} \left( \int_{0}^{x} |h(t)|^{q} dt \right)^{\frac{1}{q}} =: K \left( \int_{0}^{1} F(x,t) dt \right)^{\frac{1}{q}},$$

where

$$F(x,t) := \begin{cases} x^{-\frac{2q}{p}} |h(t)|^q, & \text{if } 0 \leqslant t < x, \\ 0, & \text{otherwise.} \end{cases}$$
 Note that  $F(x,t) \in [0,1] \times [0,1].$ 

Hölder-Minkowski inequality (see [Bahouri (2011), p.4]) states:

Let  $(X_1, \mu_1)$  and  $(X_2, \mu_2)$  be two measure spaces and f be a nonnegative measurable function over  $X_1 \times X_2$ . For all  $1 \leq q \leq p \leq \infty$ , we have

$$\left\| \|f(x_1,\cdot)\|_{L_q(X_2,\mu_2)} \right\|_{L_p(X_1,\mu_1)} \le \left\| \|f(\cdot,x_2)\|_{L_p(X_1,\mu_1)} \right\|_{L_q(X_2,\mu_2)}.$$

Then by Hölder-Minkowski inequality, we have

$$\begin{split} \|g\|_{p} &\leqslant K \left[ \int_{0}^{1} \left( \int_{0}^{1} F(x, t) dt \right)^{\frac{p}{q}} dx \right]^{\frac{1}{p}} = K \left\| \|F(x, \cdot)^{\frac{1}{q}} \|_{q} \right\|_{p} \\ &\leqslant K \left\| \|F(\cdot, t)^{\frac{1}{q}} \|_{p} \right\|_{q} = K \left[ \int_{0}^{1} \left( \int_{0}^{1} F(x, t)^{\frac{p}{q}} dx \right)^{\frac{q}{p}} dt \right]^{\frac{1}{q}} \\ &= K \left[ \int_{0}^{1} \left( \int_{t}^{1} x^{-2} |h(t)|^{p} dx \right)^{\frac{q}{p}} dt \right]^{\frac{1}{q}} \\ &= K \left[ \int_{0}^{1} |h(t)|^{q} \left( \frac{1}{t} - 1 \right)^{\frac{q}{p}} dt \right]^{\frac{1}{q}} \leqslant K \left[ \int_{0}^{1} |h(t)|^{q} \left( \frac{1}{t} \right)^{\frac{q}{p}} dt \right]^{\frac{1}{q}} \\ &= K \left[ \int_{0}^{1} |t^{-\frac{1}{p}} h(t)|^{q} dt \right]^{\frac{1}{q}} = K \left[ \int_{0}^{1} |1 - Q(t)|^{q} dt \right]^{\frac{1}{q}}. \end{split}$$

where the inequality holds since  $0 < \frac{q}{p} < 1$  and  $0 < \frac{1}{t} - 1 < \infty$  and

$$\left(\frac{1}{t} - 1\right)^{\frac{q}{p}} \leqslant \left(\frac{1}{t}\right)^{\frac{q}{p}}.$$

**Remark 2.8.** Note that q < p, then Lemma 2.1 is some kind of Inverse Inequality: Higher regularity norm bounded by lower regularity norm.

*Proof of Theorem 2.2.* To prove (2.4), our goal is to employ Lemma 2.1 and construct the formula

$$E(x^r, \Lambda)_p \leqslant \left\| x^{\frac{1}{2} - \frac{1}{p}} - \sum_{k=0}^n a_k x^{\ell_k + \frac{1}{2} - \frac{1}{p}} \right\|_p$$
, for some  $\ell_k > -\frac{1}{2}$  and  $a_k$ .

To achieve this, for any  $a_k$ ,  $0 \le k \le n$ , which will be determined later, we have

$$E(x^r, \Lambda)_p \leqslant ||x^r - \sum_{k=0}^n a_k x^{\lambda_k}||_p = \left[ \int_0^1 \left( x^r - \sum_{k=0}^n a_k x^{\lambda_k} \right)^p dx \right]^{\frac{1}{p}}.$$

By a variable transform  $x = y^{\rho}$ ,  $\rho > 0$ , which is invariant under the interval [0, 1] and  $\rho$  will be determined later, we have

$$E(x^{r}, \Lambda)_{p} \leq \left[ \int_{0}^{1} \left( y^{\rho r} - \sum_{k=0}^{n} a_{k} y^{\rho \lambda_{k}} \right)^{p} \rho y^{\rho - 1} dy \right]^{\frac{1}{p}}.$$

$$= \rho^{\frac{1}{p}} \left\| y^{\rho r + \frac{\rho}{p} - \frac{1}{p}} - \sum_{k=0}^{n} a_{k} y^{\rho \lambda_{k} + \frac{\rho}{p} - \frac{1}{p}} \right\|_{p}.$$

Let  $\rho r + \frac{\rho}{p} = \frac{1}{2}$ , we obtain  $\rho = \frac{p}{2(pr+1)}$ . Let  $\ell_k = \frac{p(\lambda_k - r)}{2(pr+1)} > -\frac{1}{2}$ , it is easy to examine that  $l_k + 1/2 > 0$ , by Lemma 2.1, we have

$$E(x^{r}, \Lambda)_{p} \leq \left(\frac{p}{2(pr+1)}\right)^{\frac{1}{p}} \left\| y^{\frac{1}{2} - \frac{1}{p}} - \sum_{k=0}^{n} a_{k} y^{\ell_{k} + \frac{1}{2} - \frac{1}{p}} \right\|_{p}$$

$$\leq \left(\frac{p}{2(pr+1)}\right)^{\frac{1}{p}} \left(1 + \frac{1}{p}\right) \left\| 1 - \sum_{k=0}^{n} b_{k} y^{\ell_{k}} \right\|_{2}.$$
(6)

Since  $a_k$  is arbitrary, hence  $b_k$  is also arbitrary. Take the infimum on the right hand side of (6) over  $b_k$ , and by Theorem 2.4, we have

$$E(x^r, \Lambda)_p \leqslant \left(\frac{p}{2(pr+1)}\right)^{\frac{1}{p}} \left(1 + \frac{1}{p}\right) \prod_{k=0}^n \frac{|\ell_k|}{\ell_k + 1} = \frac{1 + 1/p}{(2r + 2/p)^{1/p}} \prod_{k=0}^n \frac{|r - \lambda_k|}{r + \lambda_k + 2/p}.$$

**Theorem** (Part of Theorem 1.1). Let  $\Lambda_{\infty} = \{0 = \lambda_0 < \lambda_1 < \dots < \lambda_n < \dots\}$  and  $\lim_{n \to \infty} \lambda_n = \infty$ . Then  $\mathcal{M}(\Lambda_{\infty})$  is dense in  $L_p[0,1]$ ,  $2 , if and only if <math>\sum_{k=1}^{\infty} \lambda_k^{-1} = \infty$ .

*Proof.* We note that  $\mathbb{P}$  is dense in  $L_p[0,1]$ . It is sufficient to show that

$$\forall r \in \mathbb{N} = \{0, 1, 2, \dots\}, \lim_{n \to \infty} E(x^r, \Lambda_n)_p = 0 \iff \sum_{k=1}^{\infty} \frac{1}{\lambda_k} = \infty.$$

" $\Leftarrow$ " Sufficiency. Suppose that  $\sum_{n=1}^{\infty} \lambda_n^{-1} = \infty$  and  $r \in \mathbb{N} \setminus \Lambda_{\infty}$ . Note that  $0 \in \Lambda_{\infty}$ , thus  $r \geqslant 1$ . There exists an index  $k_0$  s.t.  $\lambda_k > r$  whenever  $k \geqslant k_0$ . Then

$$\lim_{n \to \infty} E(x^r, \Lambda_n)_p \leqslant \frac{1 + 1/p}{(2r + 2/p)^{1/p}} \frac{\prod_{k=0}^{\infty} |r - \lambda_k|}{\prod_{k=0}^{\infty} |r + \lambda_k + 2/p|} = C(r, k_0) \frac{\prod_{k=k_0}^{\infty} \left(1 - \frac{r}{\lambda_k}\right)}{\prod_{k=k_0}^{\infty} \left(1 + \frac{r + 2/p}{\lambda_k}\right)},$$

where

$$C(r, k_0) = \frac{1 + 1/p}{(2r + 2/p)^{1/p}} \prod_{k=0}^{k_0 - 1} \frac{|r - \lambda_k|}{|r + \lambda_k + 2/p|}.$$

Denote

$$S_1 = \sum_{k=k_0}^{\infty} \log\left(1 - \frac{r}{\lambda_k}\right), \ S_2 = \sum_{k=k_0}^{\infty} \log\left(1 + \frac{r + 2/p}{\lambda_k}\right).$$

Then  $S_1$  diverges to  $-\infty$  and  $S_2$  diverges to  $+\infty$ , leading to obtain  $\lim_{n\to\infty} E(x^r, \Lambda_n)_p = 0$ .

" $\Rightarrow$ " Necessity. Note that

$$E(x^r, \Lambda_n)_p \geqslant E(x^r, \Lambda_n)_2.$$

Then  $\forall r \in \mathbb{N}$ ,  $\lim_{n \to \infty} E(x^r, \Lambda_n)_p = 0$  gives rise to  $\lim_{n \to \infty} E(x^r, \Lambda_n)_2 = 0$ , which leads to  $\sum_{k=1}^{\infty} \lambda_k^{-1} = \infty$ .

**Remark 2.9.** The value  $\lambda_0 = 0$  can be removed. In fact, let  $\Lambda_{\infty} = \{0 < \lambda_1 < \dots < \lambda_n < \dots \}$  with  $\lim_{n \to \infty} \lambda_n = +\infty$ ,

$$\prod_{k=1}^{\infty} \left( 1 - \frac{2/p}{\lambda_k + 2/p} \right) = 0 \iff \sum_{k=1}^{\infty} \log \left( 1 - \frac{2/p}{\lambda_k + 2/p} \right) = -\infty$$

$$\iff \sum_{k=1}^{\infty} \frac{2/p}{\lambda_k + 2/p} = +\infty \iff \sum_{k=1}^{\infty} \frac{1}{\lambda_k} = +\infty.$$

Then if  $\sum_{k=1}^{\infty} \lambda_k^{-1} = \infty$ , we have  $\lim_{n\to\infty} E(1,\Lambda_n)_p = 0$ . Conversely, if  $\lim_{n\to\infty} E(1,\Lambda_n)_p = 0$ , which leads to  $\lim_{n\to\infty} E(1,\Lambda_n)_2 = 0$ , we have  $\sum_{k=1}^{\infty} \lambda_k^{-1} = \infty$ .

## 2.2.4 Conclusion and remarks.

Let  $2 \leq p \leq \infty$  and  $\Lambda = {\lambda_k}_{k=0}^n$  with  $\lambda_k > -1/p$ . Then for any r > -1/p, we have

$$E(x^r, \Lambda)_p \leqslant \frac{1 + 1/p}{(2r + 2/p)^{1/p}} \prod_{k=0}^n \frac{|r - \lambda_k|}{r + \lambda_k + 2/p}.$$

## A Variant of Dense Property.

(see also Section 5 of Chapter 11 in [Lorentz (1993)])

Let  $C[0,+\infty]$  be the space of continuous functions on  $[0,+\infty]$ , which have a finite limit for  $t\to\infty$ . Exponential sums

$$\sum_{k=0}^{n} a_k e^{-\lambda_k t}$$

approximate arbitrarily closely each function  $f \in C[0,+\infty]$  if and only if  $\lambda_0 = 0$ ,  $\lambda_k > 0$  for  $k \ge 1$  and  $\sum_{k=1}^{\infty} \lambda_k^{-1} = \infty$ .

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